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Evolving Wavelet Compression Strategies

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ABSTRACT

Wavelet theory provides an attractive approach to signal and image compression. This work investigates a new approach for wavelet transform coefficient selection for efficient image compression. This approach is based on the stochastic optimization of wavelet scale thresholds. Experimental results are compared with results from previously published wavelet image compression strategies.

1. Introduction

Wavelets, a family of basis functions, are dilations and translations of a single initial function exhibiting a constant shape. Wavelets originated from the analysis of seismic data by J. Morlet. Wavelets basis sets can be orthogonal or non-orthogonal, and each wavelet can have compact or infinite support. Orthogonal wavelets, such as the Haar and four-coefficient Daubechies wavelets, provide the capability of decomposing images into multiresolution representations via the wavelet transform[1]. Wavelets, via the wavelet transform, provide an efficient approach for the compression of images.

Traditionally, image transform coding or compression methods, such as the discrete cosine transform, rely on high energy compaction with an $n \times n$ passband coefficient selection criterion. The wavelet transform generally results in poor energy compaction, so an alternative strategy is required for wavelet coefficient selection. This paper investigates a stochastic optimization approach for wavelet coefficient selection.

1.1. Wavelet Transform Theory

Performing the Fourier transform decomposes an image into a frequency representation and allows an analyst to determine if a particular frequency is present, but does not provide any spatial information. The wavelet transform, on the other hand, results in a spatial-frequency representation that has good localization in both domains. Wavelets can be orthogonal or overcomplete, but since we are interested in compressing the image, we do not want to transform the image into more coefficients than necessary to completely characterize the image. Therefore, we use an orthogonal wavelet (the Haar wavelet) in this research.

An orthogonal wavelet is determined by specifying a lowpass filter that satisfies

$$\begin{aligned} &H(0) = 1 \\ &|H(\omega)|^2 + |H(\omega + \pi)|^2 = 1 \end{aligned} \tag{1}$$

where $H(\omega)$ represents the Fourier transform of the filter h. The corresponding highpass filter g is defined as

$$G(\omega) = e^{-j\omega} H^*(\omega + \pi) \tag{2}$$

where $H^*(\cdot)$ is the complex conjugate of $H(\cdot)$. For the classic orthogonal wavelet, the Haar, $h(0) = 1$, $h(1) = 1$, and h is zero everywhere else. The interpolation order of the wavelet increases with the length of the wavelet. Wavelet selection can affect the quality of the reconstruction. We are interested, however, in the effects of stochastically optimizing the compression thresholds, and therefore a single wavelet basis will be used in this investigation.

The wavelet transform filters the data and results in a lowpass, or blurred, version of the original, and a highpass, or detailed, version. The lowpass image is then filtered to produce a blurred and detail image of it. Because the wavelet transform we are using is separable, the image wavelet transform can be implemented as successive one-dimensional transforms of the row and columns. The resulting image has a horizontal detailed image, a vertical detailed image, a diagonal detailed image, and a blurred image.

Given a signal f, the decomposition is

$$f_J^B(n) = \sum_k h(2n-k) f_{J+1}^B(k) \tag{3}$$

$$f_J^D(n) = \sum_k g(2n-k) f_{J+1}^B(k) \tag{4}$$

where f_J^B is the blurred version of f at scale J and f_J^D is the detail signal at scale J. One can reconstruct f from its projections, defined as

$$f_J^B(n) = 2\sum_k \tilde{h}(n-2k) f_{J-1}^B(k) + 2\sum_k \tilde{g}(n-2k) f_{J-1}^D(k) \tag{5}$$

where $\tilde{h}(k) = h(-k)$ and $\tilde{g}(k) = g(-k)$.

1.2. Wavelet Compression Techniques

Image compression after performing the wavelet transform is achieved by selecting a set of coefficients from the wavelet representation to keep. Those coefficients not selected are set to zero. The number selected is based on the maximum mean-squared error (MSE) acceptable, the compression ratio needed, or a combination of both. The coefficients selected are then coded using an entropy-based encoder that stores the value of the coefficient and its location within the current scale.

Different sets of retained coefficients can result in drastically different image reconstructions. The traditional method for selection is simply a passband filter of some height and width that passes a rectangular region of the transformed data and sets the rest to zero. The wavelet transform does not compact energy into a particular region, making the passband approach suboptimal. DeVore et al[2] show that this is indeed the case, and present an algorithm that keeps the highest N coefficients and discards the rest. Argast et al[3] demonstrate that coefficients from lower resolution scales affect a larger part of the image than coefficients in the high resolution scales. Argast presents an algorithm for selecting coefficients based on a logarithmic threshold, where the threshold of each scale is twice the threshold of the previous lower resolution scale. This compression strategy is given as:

$$
\begin{array}{l}
\textit{for } J = S \textit{ to } 1 \,\{ \\
\qquad \textit{for each element } k \textit{ in scale } J \\
\qquad \textit{if } CR\% = GOAL \textit{ then stop} \\
\qquad \textit{else} \\
\qquad\qquad \textit{set } c_k = \begin{cases} 0 & \textit{if } |c_k| < 2^J T \\ c_k & \textit{otherwise} \end{cases} \\
\}\, \textit{end}
\end{array}
$$

where c_k is a transform coefficient, $CR\%$ is the current compression percentage, T is a constant weight factor, and J and S are respectively the current and total wavelet scales. T is set initially at a constant (0.01 in their paper), and adjusted so that the compression ratio can be met. While using this approach results in a lower mean-squared error in the reconstructed images for a given compression than DeVore's algorithm, it was still not known if it was the optimal set of thresholds. In this paper, we attempt to answer this question by stochastically optimizing the threshold values.

1.3. Stochastic Optimization

Since the 1950's, random (or stochastic) search techniques have been used for function optimization. Random search strategies are competitive with traditional search strategies (such as gradient search techniques) when the cost or objective function is expensive or difficult to compute, or when the function to be minimized has many suboptimal solutions (local minima). Other advantages, enumerated by Karnopp[4], include the ease of programming, inexpensive realization of possible solutions, as well as flexibility in the expression of the criterion function.

Stochastic optimization techniques are based on either a single point or multiple agent algorithms. Single point algorithms include the random walk and the method of Solis and Wets[5]. Solis and Wets[5] provide convergence proofs for single agent random search strategies. A convergence proof for the evolutionary programming algorithm, the multiple agent search strategy developed by Fogel[6], is given by Fogel[7]. Under very weak assumptions, both Solis and Fogel respectively show that a single and a multiple agent random search technique will probabilistically converge to a region about the minima of the function.

To increase convergence efficiency, variants of the EP algorithm have been developed[8,9]. This work imbeds the method of Solis and Wets into the traditional evolutionary programming paradigm. The parent models not only produce a single offspring by way of the stochastic process, but are also modified by the Solis and Wets algorithm. This approach, in the nomenclature of Bäch and Schwefel[10] is as follows:

$$
\begin{array}{l}
k = 0; \\
\textit{initialize: } P(0) = \{\boldsymbol{a}_1(0), \ldots, \boldsymbol{a}_\mu(0)\} \\
\qquad \textit{where } \boldsymbol{a}_i = \left(x_j, \forall j \in \{1, \ldots n\}\right) \\
\textit{evaluate: } P(0){:}\;\; \Phi(P(0)) = \left\{\Phi(\boldsymbol{a}_1(0)), \ldots, \Phi(\boldsymbol{a}_\mu(0))\right\} \\
\textit{do } \{ \\
\qquad \textit{mutate: } \boldsymbol{a}'_j(k) = m'\left(\boldsymbol{a}_j(k)\right) \qquad \forall j \in \{1, \ldots, \mu\} \\
\qquad \textit{evaluate } P'(k){:}\;\; \Phi(P'(k)) = \left\{\Phi(\boldsymbol{a}'_1(k)), \ldots, \Phi(\boldsymbol{a}'_\mu(k))\right\}
\end{array}
$$

$$\begin{array}{l} \textit{modify parents: } P''(k) = \left\{ a_j''(k) = s'\left(a_j(k)\right) \quad \forall j \in \{1,\ldots,\mu\} \right\} \\ \textit{select: } P(k+1) = s_{\{q\}}\left(P''(k) \cup P'(k)\right) \\ k = k+1 \\ \} \textbf{ while } \left(\iota(P(k)) \neq \textit{true}\right) \end{array}$$

The population is instantiated with μ individuals $a_j \, \forall j \in \{1,\ldots\mu\}$. The mutation operator $m'(\cdot)$ is applied to each individual, according to the random perturbation scheme

$$a_i' = a_i + \sigma_i \cdot N(\mathbf{0},\mathbf{I}) \tag{6}$$

$$\sigma_i = \sqrt{n^{-1} \cdot \Phi(a_i)} \tag{7}$$

where n is the dimensionality of a, and $\Phi(\cdot)$ is the criterion function.

2. Evolving Compression Strategies

The optimal wavelet compression strategy is, of course, a function of two (interacting) aspects, the compression ratio and the image quality of the compressed image. The criterion function $\Phi(\cdot)$ should measure these two aspects of the compressed image. Measuring the compression ratio of the compressed image is straightforward. Although image quality is a subjective facet of an image, a widely used objective measure of image reconstructive quality is the mean-squared error between the reconstructed and original images. Maximizing the compression ratio penalty, denoted as P_c, while minimizing the reconstructed MSE provides the foundation for the criterion function:

$$\Phi(a) = \frac{1}{m^2} \sum_{l=1}^{m} \sum_{k=1}^{m} \left(i_{l,k} - r_{l,k}\right)^2 + P_c \tag{8}$$

To derive the form of P_c, experiments were conducted using threshold, linear, and exponential functions to compute the compression penalty. In our investigation, P_c was chosen as an exponential function of the compression ratio percentage $CR\%$ and the percentage goal (Eq. (9)). The penalty function biases the optimization algorithm to guarantee the achievement of the desired compression.

$$P_c = \begin{cases} 100e^{CR\%/GOAL} & \textit{if } CR\% < Goal \\ 0 & \textit{if } CR\% \geq Goal \end{cases} \tag{9}$$

The algorithm used to zero coefficients is given as

$$\begin{array}{l} \textit{for } J = 1 \textit{ to } S \\ \quad \textit{for each element } k \textit{ in } J \\ \qquad \textit{set } c_{k,j} = \begin{cases} 0 & \textit{if } \left|c_{k,j}\right| < T(J) \\ c_{k,j} & \textit{otherwise} \end{cases} \end{array}$$

where $T(J)$ is the stochastically determined threshold for the wavelet transform's Jth scale. Each vector T therefore represents a wavelet compression strategy, and the determination of the optimal strategy is the goal of the stochastic optimization process.

3. Results

Images where selected from the Georgia Tech. University image library at *gatech.edu*. Wavelet compression strategies were evolved for three contrast-enhanced 512×512 gray scale images, each with eight bits per pixel. Contrast stretching was performed on each image before analysis. For each image, the compression ratio was set to 50:1 ($GOAL = .02$). Figure 1 displays the MSE and compression value of the best strategies for the first 100 iterations of the optimization process.

For all images, the number of parent strategies in the stochastic optimization process was set to five. Although five is low for the typical stochastic optimization problem, the number proved to be more than adequate for determining the image compression strategies. This does not mean that the solution space was a simple well, as local minima were discovered in the experimental process. By adjusting the value for the maximum allowable standard deviation in the Solis and Wets algorithm, all local minima encountered were escaped by the stochastic optimization process. For all images tested, the stochastic optimization process converged to a solution within 500 iterations.

The threshold values of the optimal strategy (the optimal T vector) after 500 iterations are respectively graphed and tabulated in Figure 2 and Table 1. It is important to note that the values for the lower scales (scales 0 through 3) are below all coefficients in those scales, and therefore very few, if any, coefficients in these scales are zeroed. It is interesting that, for the higher scales, each scale value is approximately double the value of the previous scale for all images tested.

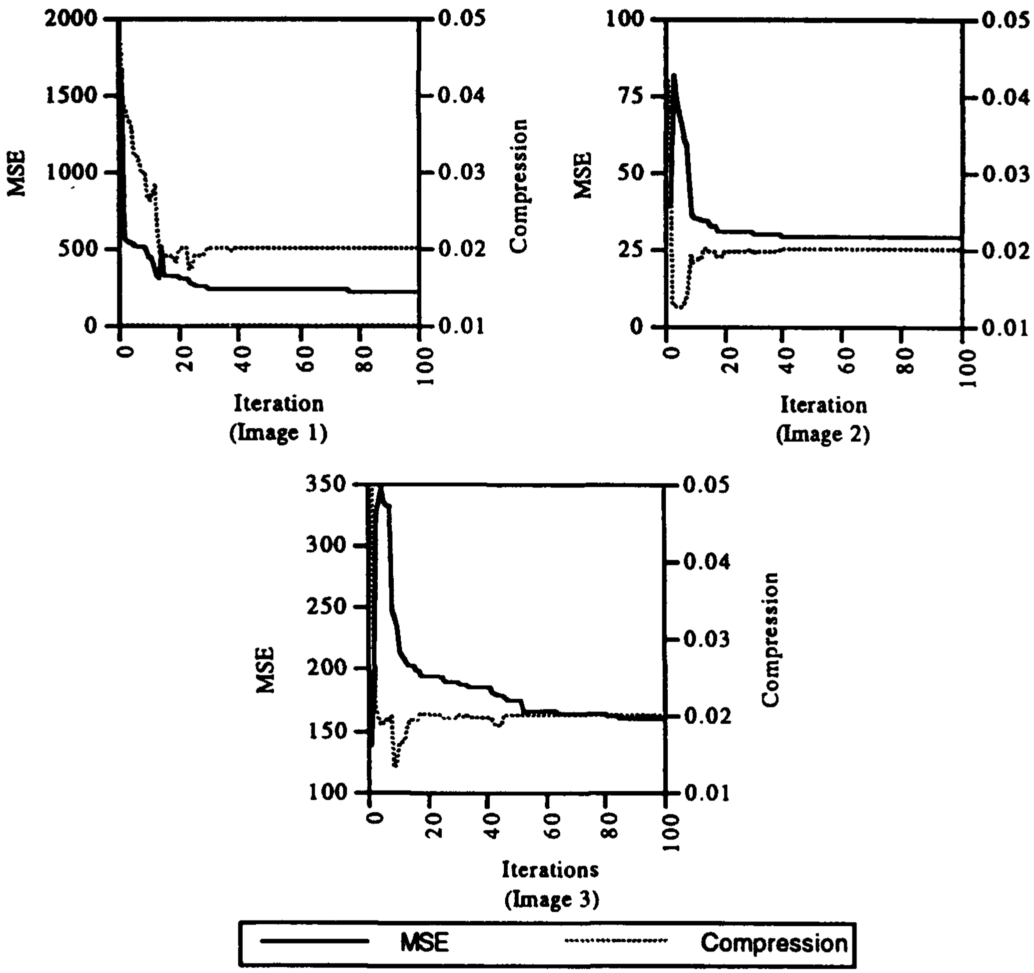

Figure 1. Stochastic optimizing behavior for first 100 iterations for each image.

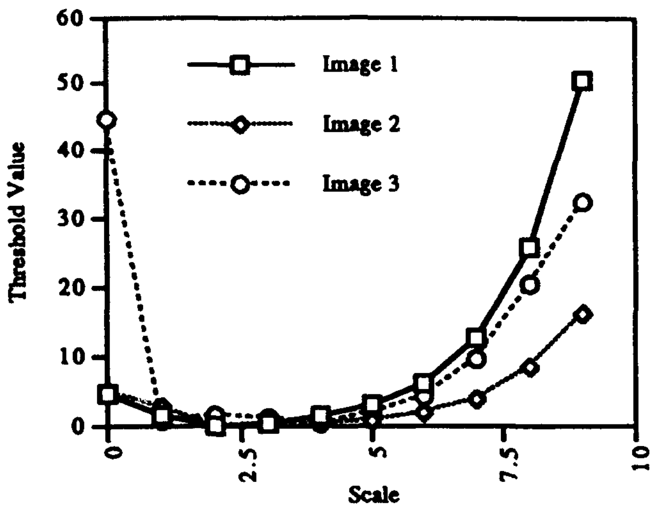

Figure 2. Evolved threshold strategies for images.

Table 1. Thresholds for optimal evolved strategy

Image	0	1	2	3	4	5	6	7	8	9
Image 1	4.9358	1.6176	0.2637	0.5912	1.7359	3.1925	6.5342	12.707	25.924	50.522
Image 2	5.1373	3.0283	0.3044	0.4055	0.4272	1.1291	2.0126	4.1380	8.7490	16.519
Image 3	44.780	0.9408	1.6479	1.4099	0.5161	2.1493	4.4556	9.7358	20.457	32.621

A comparison of the stochastically determined compression strategy obtained for normal and contrast versions of a single image is shown in Table 2. The same between-scale relationship of the threshold values found in the enhanced images is displayed in the non-enhanced image.

Table 2. Comparisons of threshold values for same image

Image	0	1	2	3	4	5	6	7	8	9
Normal	3.9590	3.8628	1.6142	0.7182	0.5840	1.5741	4.1666	9.2286	16.775	36.951
Enhanced	4.9358	1.6176	0.2637	0.5912	1.7359	3.1925	6.5342	12.707	25.924	50.522

For each image, a comparison of the MSE of the reconstructed images using the evolved compression strategy and the algorithms of DeVore and Argast was performed. The results are shown in Table 3. As shown, for all images compressed and restored, the stochastic strategy outperforms the deterministic algorithms.

Table 3. MSE Comparison for Compression Strategies

Compression Algorithm	*Image 1*	*Image 2*	*Image 3*
DeVore (algorithm b)	586.187	59.997	277.525
Argast	247.282	33.582	160.840
Stochastic	221.339	28.786	150.938

5. Conclusions

These results demonstrate that a stochastic optimization technique can produce optimal threshold-based strategies for wavelet-based image compression. For all images tested, the resulting strategies produce results exceeding present deterministic algorithms. More importantly, a stochastic approach can provide insight into the relationship between compression coding and the information content of the wavelet scales.

Future research in stochastic optimization of wavelet compression algorithms exists in the determination of the general relationship between the energy of the image and the threshold values required for optimal compression, and the statistical properties of the threshold values and their interscale relationship. Another independent area of research is the stochastic optimization of the wavelet basis function selected for the compression and reconstruction of an image. Our future work will address both these areas of research.

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